Recent Macroeconomic Stability in China

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Abstract

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JEL Classification: C33 ; E31 ; E32 ; J00.

Keywords: Great Moderation; Output Volatility; China.

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Abstract

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1. Introduction

The striking reduction of output volatility in most industrial economies since the early 1980s, also known as the Great Moderation, has attracted extensive attention in recent years. Starting with the work of McConnell et al. (1999), a number of researchers investigate the sources of the sharp decline in macroeconomic volatilities. However, substantial disagreement on the origin of the Great Moderation continues. Clarida et al. (2000) and Boivin and Giannoni (2006) claim that good policies, such as improved monetary policies, have tamed the business cycle. Meanwhile, McConnell et al. (1999) and Kahn et al. (2002) suggest that improved business cycle practices, such as inventory management and financial innovations,[1] account for a significant fraction of the reduction in output volatility. Simon (2000) and Stock and Watson (2002) argue that the decline in output volatility may simply reflect milder shocks impacting the economy. More recently, Justiniano and Primiceri (2008) show that investment-specific technology shocks account for most of the sharp decline in output volatility.

This sharp decline is not a phenomenon unique to western economies. Some studies note that China has also experienced a substantial reduction in output volatility since the mid-1990s (Brandt and Zhu, 2000; He et al., 2009; Laurenceson and Rodgers, 2010; Du et al., 2011). However, so far little is known about the reasons behind China's economic moderation.

This paper adds to the existing literature by analyzing the time-varying volatility of the macroeconomic fluctuations in China, which is the largest emerging market economy and plays an increasingly important role in the world economy. The case of China is interesting for two reasons. First, different from western economies, China's moderation occurred with an exchange rate peg, capital control and financial repression. That western economies and China, with such diverse economic structures and macroeconomic environments, experienced a comparable volatility reduction provides an ideal venue for examining the driving force of this increasing macroeconomic stability.[2] Second, output volatility reduction is usually associated with relatively lower average growth rates of output in developed countries. China has experienced a substantial reduction in output volatility since the mid-1990s, but its economy has continued to grow rapidly. Over the past three decades, the growth rate has been, on average, about 10 percent, and has been

[1] Dynan et al. (2006) find evidence that financial innovation is a likely contributor to the mid-1980s stabilization.

[2] Ahmed et al. (2004) report that the standard deviation of the GDP growth rate halved from the 1960-1983 period to the 1984-2002 period. Based on the Chinese data, we find that the standard deviation of the GDP growth rate is 4.02 between 1979 and 1994. After 1994, the standard deviation halves, falling to 1.96. See Table 1 for more detailed summary statistics.

much higher than that of all western countries. Studying Chinese macroeconomic volatilities can further clarify the relationship between economic growth and volatility.

To understand the driving force of recent Chinese macroeconomic moderation, we use the two-step strategy developed by Ahmed et al. (2004). In the first step, a spectrum analysis is employed to decompose the variances of macroeconomic variables by different frequency bands. The frequency domain method allows us to associate the volatility shifts with each possible moderation explanation.[3] We then identify a variety of VAR models to complement the frequency domain analysis in the second step.[4] The counterfactual analysis based on these VAR models allows us to determine whether the volatility reduction is due to changes in economic structure or changes in random shocks.

The main finding of this paper is that Chinese macroeconomic volatilities have experienced a substantial decline since the mid-1990s. In particular, we find that most reduction is due to milder shocks hitting the economy in the post-1994 period. Our results show that the post-1994 shift in spectrum is proportional across all frequencies for a wide range of macroeconomic variables, including the aggregated real GDP growth rate. Improvements in policy implementation and better business practices that may change the economy's response to shocks, rather than the exogenous shocks themselves, do not have a significant impact on volatility reduction. The estimates of the VAR analysis corroborate this finding. Although structural breaks in the coefficients across the two periods are found, supporting the importance of changes in the economic structure, the reduction in the innovation variance still plays a dominant role in driving output volatility.

Our results call into question the sustainability of the growth of the Chinese economy. Despite a remarkable economic growth performance over the last three decades, the Chinese economy still relies on a strategy of incremental reform and extensive growth,[5] which renders it far from a market-oriented economy. As Prasad (2008) suggests, Chinese growth strategy has reduced the flexibility of the economy to withstand and recover against any large economic shock. Although

[3]Ahmed et al. (2004) show that the spectrum shift at the business-cycle frequency reflects changes in monetary policy while relevant changes in business practices are more likely to be associated with relatively high frequencies. Finally, shifts of innovation shock generate a proportional change in the spectrum at all frequencies.

[4]Our estimation procedure closely follows the methodology of Ahmed et al. (2004). However, we include estimations of structural VAR models in addition to the reduced-form VAR analysis. We are indebted to one of the referees making this point.

[5] A growth pattern is characterized by using the expansion of inputs to promote economic growth. The popular view that China has followed an extensive growth model (for example, Wolf, 2011) has been challenged by the evidence of Zhu (2012), who shows that aggregate productivity growth has been the major driving force of China's growth since 1978. However, Zhu (2012) admits that many obstacles and distortions exist during China's economic reform, which may prevent productivity growth from being realized. Using firm-level data, Hsieh and Klenow (2009) show that total factor productivity gains about 30 to 50 percent if distortions in Chinese factor productivity are reduced to the U.S. level.

the Chinese economy has maintained a high growth rate with low volatility, our results show that reduced random economic shocks, or just good luck, may account for much of the stability of the Chinese economy, while good policy and good business practices, which are more likely to provide ongoing economic stability, [6] have only played minor roles in the decline in macroeconomic volatilities. Unfortunately good luck can become bad luck in the future. Reforms to improve policy effectiveness and business cycle practices are crucial for China to prepare for potential future economic shocks, and to maintain sustainable economic growth.

The paper is organized as follows. Section 2 presents evidence and possible explanations of the moderation of macroeconomic volatility in China. Section 3 describes our frequency domain analysis. A variety of VAR models are employed to address the source of the reduction in fluctuations in Section 4. Conclusions and policy discussions are given in Section 5.

2. Macroeconomic Fluctuations and Theoretical Considerations

2.1 Volatility of the Chinese macro-economy

The most striking feature of the Chinese economy from the past three decades is its impressive growth during the reform period. Fluctuations in the Chinese macroeconomic variables reduced substantially from the mid-1990s (see Brandt and Zhu, 2000; He et al. 2009; Du et al. 2011; He et al. 2013). To investigate how this moderation came about over the last three decades, we now review the patterns of key macroeconomic time series from the first quarter of 1979 to the fourth quarter of 2010. Our data are drawn from the CEIC database, except for the quarterly real GDP growth rate before 1994 which is obtained from Abeysinghe and Rajaguru (2004). Our analysis is based on quarterly data after removing the trend and seasonal components.[7] Specifically, real variables are transformed into growth rates (quarterly year-on-year growth rate), and prices are transformed into inflation rates (quarterly year-on-year growth rate). Definitions and specific transformations used for each series are reported in the Appendix.

Figures 1 and 2 provide graphical evidence for the declining volatility of output and inflation (the growth rate of the consumer price index (CPI)). Figure 1 shows that the real GDP growth rate fluctuates at around 10 percent, with a range of 16 percent in 1985 to zero percent growth in 1989.

[6] For example, the improvement of inventory management techniques may cause structural changes in production areas and permanently reduce their variability.

[7] When quarterly data is unavailable, we used the Chow-Lin method (1971) for temporal disaggregation to transform each series from annual data into quarterly data.

The growth rate rebounded to 14 percent in 1994. Since then, however, the output growth rate has been markedly less volatile, moving within a band of 6.2 and 13.8 percent. The CPI inflation rate also shows large fluctuations before 1994, with the bottom at 1 percent in 1990Q3 and the peak at 25 percent in 1994Q4. Thereafter, the inflation rate moderates substantially within a range of -1 percent to 8 percent, most of the time. The CPI inflation rate drops dramatically with deflation emerging in early 1998 and lasting until 2002. Positive annual inflation appears in 2003 and peaks at 8 percent in 2008Q1.

< Insert Figure 1 here >

< Insert Figure 2 here >

Table 1 reports the basic summary statistics of some Chinese macroeconomic variables. Significant volatility reductions are found when standard deviations are compared from before and after the 1994 break date (denoted as Period I and Period II hereafter). The magnitude of the decline is striking, and is comparable with the volatility reduction in the U.S. Although the average growth rates do not show an evident decline, all series were less volatile in the second (post-1994) period. Between 1979 and 1994, the standard deviations of the real GDP growth rate and the CPI inflation rate were 4.02 and 7.53, respectively. After 1994, they fell to 1.96 and 4.77, respectively.[8] On the production side, the standard deviations of Period II range from 1.94 (primary industry output) to 2.34 (secondary industry output), and are quite different to Period I where primary industry and secondary industry output were 3.97 and 7.66, respectively. On the demand side, Period II standard deviations range from 2.32 (inventory) to 10.67 (investment), much lower than those in Period I.

The reduction in volatility is reflected in other variables as well. For example, the fluctuation in the nominal effective exchange rate (NEER) shows a clear reduction in Period II. In contrast, the standard deviation of interest rate increases in Period II, implying that China gradually increased the flexibility of the interest rate to strengthen the effectiveness of monetary policy.

< Insert Table 1 here >

2.2 Potential sources of economic moderation in China

[8] The standard deviation of U.S. GDP growth falls from 4.4 percentage points in the 1960-1983 period to 2.3 percentage points in the 1984-2002 period (Ahmed et al., 2004).

In the previous section, we document a widespread volatility reduction across Chinese macroeconomic variables. To investigate the driving force of this reduction, we follow the literature (Summers, 2005) and consider three possible explanations, namely, good policy, good practice and good luck.

Boivin and Giannoni (2006) suggest that better implementation of monetary policies tames economic volatility. They argue that a successful monetary policy will create a good economic environment with low and stable inflation, which in turn removes uncertainty from firms' production; it also increases the flexibility of policy makers in responding to unforeseeable events, leading to a lower volatility of output growth.

In China, economic moderation occurred soon after several important changes of the Chinese monetary system. The conduct of monetary policy changed substantially with massive reforms since 1994. The pre-1994 period can be characterized as having used administrative controls for monetary policy, in the sense that an administrative credit plan, rather than the interest rate, served as the principal instrument for the central government to control the banking system's credit allocation. Under this plan, the central government centralized credit allocation procedures and eliminated most banks' discretion in credit allocation. This involved putting quotas on the amount of lending available, severely restricting the flow of funds outside the credit plan, which lead to a severe efficiency loss in policy implementation (Brandt and Zhu, 2000). For example, when government adopts an expansionary policy and loose credit, investment and demand for funding usually go up. However, the interest rate is not market-determined in China, so it cannot rise to lower investment and increase savings. This leads to an overheating economy and a high inflation rate, or an unstable economy. Since 1994, the Chinese government has carried out market-oriented reform to increase the effectiveness of monetary policy. The swap market and official exchange rate market were unified to allow the People's Bank of China (PBC) to influence the exchange rate through market operations. To develop more market-oriented monetary tools, the PBC introduced rediscounting and open market operations in 1995 and 1996, respectively. The interbank interest rate system was established in 1996 and the credit quota system was scrapped in 1998. Since then, most interest rates have been gradually liberalized to enhance interest rates as a monetary transmission channel. In 2005, China further reformed its exchange rate arrangement and allowed the RMB to float in reference to a basket of world currencies rather than be directly pegged to the U.S. dollar.[9]

With more flexible and potent policy tools, we expect monetary policy to stabilize prices and promote economic growth in a more efficient manner. However, the effectiveness of these policy instruments is open to question. Mehrotra (2007) finds that the interest rate, as a monetary policy tool, has little or no effect on the Chinese economy. He et al. (2013) employ a factor-augmented VAR analysis to investigate the effectiveness of several important monetary policy tools, and find that market-based policy instruments are only moderately effective. As Prasad (2008) suggests, China's gradual reforms of its financial system have been deficient and have led to an underdeveloped financial market. In particular, although reformed several times, the RMB exchange rate still has little de facto flexibility. This inflexible currency regime limits the independence of China's monetary policy, and results in extensive overuse of administrative tools in its economy (Goodfriend and Prasad, 2007).

In addition, several researchers have argued that good business cycle practices, such as improved inventory management and financial innovation can reduce output volatility. Kahn et al. (2002) suggest that firms usually make production decisions before the real demand for their products is known. Better information and inventory management can increase the flexibility of production, lowering the volatility of goods production. Meanwhile, financial innovation can enhance the ability of households and firms' to access credit resources, facilitate risk sharing and therefore better smooth their expenditures over fluctuations in the business cycle.

The hypothesis of better practices appears to be an important candidate in explaining China's moderation. China has implemented gradual reforms towards a market economy since 1978. Over the last three decades, the introduction of foreign capital, advanced technologies and management skills has improved operational efficiency and contributed to China's extraordinary economic growth. Especially after Deng Xiaoping's Southern Tour in 1992, China accelerated its market-oriented economic reforms (Naughton, 1996). In the post-1994 period, waves of privatization have permeated China's industry. A large number of private firms have emerged and play an increasingly larger role in the Chinese economy. Entrepreneurs in non-state-owned firms,

[9] On August 9, PBC Governor Zhou Xiaochuan revealed that the major currencies constituting the basket are the U.S. dollar, the euro, the yen, and the Korean won. These currencies are selected because of the importance of their economies to China's current account. However, the actual weights on these currencies were not announced. Frankel (2009) provided an estimation that the weight on the dollar is about 60% and that the weight on the euro had risen to 40% by mid-2007.

being profit maximizers, are more likely to employ new technology and advanced inventory management skills to optimize production procedures and make the highest returns.[10] As firms become more production efficient, they are better able to weather economic fluctuations, reducing production volatility. During the same period, the financial market experienced a substantial change as well. Two domestic stock exchanges (Shanghai Stock Exchange and Shenzhen Stock Exchange) were established in 1990 and grew very fast.[11] Almost concurrently, the real estate market went from being nonexistent to being comparable in size to the stock market. Meanwhile, non-state-owned banks and other financial institutions were allowed to expand their business within China. This technological progress and financial innovation allowed firms and consumers to better cushion themselves against any large economic shock.

Although these transitions have been encouraged by high and relatively stable economic growth, each has brought with it some challenges. Large state-owned banks still dominate China's financial system. They tend to channel cheap credit to SOEs, and distort incentives for investment. Meanwhile, small- and medium-sized firms in the private sector find it difficult to raise funds in the formal financial market.[12] This hampers innovation and entrepreneurship. Securities markets are inefficient as prices are not driven by the fundamental value of corporations. Expropriations of minority shareholders are prevalent due to poor minority investor protection (Morck et al., 2000). There is a large amount of speculative investment in the real estate sector. As most funds are from state-owned banks and SOEs, investors underestimate the risks of a housing bubble, and believe that the government will provide a bailout in the event of a bubble bursting. These deficiencies limit the availability of financial instruments that enable firms and investors to manage their risks,[13] and limit the effectiveness of macroeconomic policies. Incentives to manage risks are also depressed.

Finally, it is also possible that the general fall in the volatility of several key variables is entirely due to good luck (Stock and Watson, 2002). That is, the moderation of economic performance is entirely due to a reduction in the number of random shocks hitting the economy. This hypothesis is also a promising explanation for China's moderation. The Chinese economy

[10] As the state owns SOEs, and delegates its control to enterprise's managers, the separation of ownership and control gives managers less incentive to maximize profits by streamlining the production process (Lin et al., 1998).
[11] At the end of 2011, the total market capitalization of SHSE and SZSE ranked second in the world.
[12] Allen et al. (2005) argue that the private sector relies primarily on informal financing channels, such as internal funds, trade credits and financial resources from family and friends.
[13] Du et al. (2011) find that the extent of risk sharing through financial intermediaries and capital markets in China is very limited.

was highly volatile from the 1980s through the early 1990s, during which it was subject to several unusually large shocks, such as the failure of the "price system breakthrough" in 1988 and the Tiananmen Square events of 1989. From the mid-1990s until recently, China had neither experienced any similar crises nor a sharp recession. In the sense that the shocks hitting the Chinese economy have been smaller than before, the Chinese economy has simply experienced good luck.

3. Frequency Domain Analysis

3.1 Methodology

We employ frequency domain analysis to decompose a number of key economic variables of the Chinese economy into spectra, which enables investigation of the variability of different frequency components. This decomposition is possible because any covariance-stationary process $\{x_t\}_{t=-\infty}^{\infty}$ has both a time-domain representation and a frequency-domain representation; any feature of the data can be equivalently described by the two representations.

For any frequency ω, the population spectrum $g(\omega)$ for $\{x_t\}_{t=-\infty}^{\infty}$ can be defined by

$$g(\omega) = \frac{1}{2\pi}\sum_{j=-\infty}^{\infty}\gamma_j \cos(j\omega) \tag{1}$$

with γ_j as the population autocovariance function. The variance of x_t could be decomposed as

$$\mathrm{var}(x_t) = 2\int_0^{\pi} g(\omega)d\omega \tag{2}$$

where spectrum $g(\omega)$ is interpreted as the contribution to the total variance at period $\frac{2\pi}{\omega}$. Accordingly, for any given frequency range $0 \le a < |\omega| < b \le \pi$, the variance attributed to these frequencies is captured by the integrated spectrum $G(a,b)$, given by

$$G(a,b) = 2\int_a^b g(\omega)d\omega\,. \tag{3}$$

We define the normalized spectrum as $\frac{g(\omega)}{\sigma^2}$ and its integrated version as

$$\tilde{G}(a,b) = 2\int_a^b \frac{g(\omega)}{\sigma^2}d\omega$$

where σ^2 is the total variance across all frequencies as defined in Equation (2). The normalized spectrum gives the fraction of variance attributable to a certain frequency, ω.[14]

The whole spectrum can be separated into three frequency bands, namely low, business cycle and high (Ahmed et al., 2004). The business cycle is assumed to last between 6 quarters and 32 quarters, corresponding to a frequency range between $\pi/16$ and $\pi/3$. The cycles longer than 32 quarters (with frequency ω smaller than $\pi/16$) will fall into the low-frequency range, and cycles shorter than 6 quarters (with frequency ω larger than $\pi/3$) are classified as of the high-frequency range.

By decomposing the spectrum into three frequency bands, we can evaluate the sources of moderation by inspecting the volatility decline in different bands. First, as improved policy acts to dampen the business cycle, the spectrum in the business cycle frequency should decline disproportionately in the second sample period. Second, better business practices should enhance production productivity, inventory management and investment efficiency. These improvements are more likely to smooth output on a quarter-by-quarter basis. For instance, a better inventory system can match output to final sales more efficiently leading to a reduction of economic fluctuations, primarily in the high-frequency band. Finally, the good luck hypothesis expects that there is no change in the structure of the economy so the plunge in volatilities is attributable to a reduced variance of exogenous shock. This should produce a proportional decline in the spectrum at all frequencies. By inspecting the reduction in different frequency bands, the source of moderation in the Chinese economy in the post-1994 period can be identified.

The spectrum analysis approach is illustrated in Figures 3 and 4. In Figure 3, the upper panel depicts the spectrum of real GDP growth rate, while the lower panel illustrates the normalized spectrum. The upper graph shows the spectrums in the two periods. It shows that both spectra display the typical shape of an economic variable, peaking at low frequency and gradually declining as it moves toward the business cycle frequency. These skewed shapes indicate that longer-term fluctuations (i.e., fluctuations in the lower frequency bands) contribute most to the variance of real GDP growth rate. In addition, the upper graph shows an evident downward shift of spectrum in the post-1994 period, implying a decline in the volatility of GDP growth rate. The drop in output volatility primarily occurs at the business cycle frequency level. However, the normalized spectrum shows the two sample periods with similar patterns across all frequencies.

[14] See the Appendix to Ahmed et al. (2004) for more detailed econometric methodology.

The post-1994 spectrum is only slightly lower in the low frequency, is approximately equal in the business cycle frequency and is slightly higher in the high frequency. The similarity suggests that the moderation might be largely due to a shrinkage of the innovation variance.

The spectrum patterns of inflation in Figure 4 also lend support to the good luck hypothesis. The upper panel shows a substantial downward shift of the spectrum of the inflation rate, with the greatest reduction concentrated in the low and business cycle frequencies. However, when the spectrum is normalized, the lower panel of Figure 4 shows that the post-1994 spectrum has a similar pattern to that of the pre-1994 period. The post-1994 spectrum is only slightly lower in the business cycle frequency. Hence, evidence of inflation also suggests that smaller innovation shocks may account for much of the reduction in volatility of the second period.

<Insert Figure 3 here>

<Insert Figure 4 here>

3.2 Estimation results

We report the results for the real GDP growth rate, inflation and the selected components of GDP. In each case, we assume that a structural break exists at the end of 1994, such that volatilities are moderated from 1995.[15]

The test results are reported in Table 2 and Table 3. In each of the three frequency ranges, we report the integrated spectrum estimates (integrated normalized spectrum estimates) for Period I and Period II in the third and fourth column of Table 2 (Table 3), respectively. The last two columns give the test statistics of the null hypothesis that the spectrums of the two periods are equal, and the corresponding marginal significance level (*p*-value) for the test of the null hypothesis.

Table 2 reports the estimation results of the integrated spectrum of GDP growth rate. Though the integrated spectrum shrinks substantially from Period I to Period II, the reduction is significant only for the business cycle's frequency interval, based on the *p*-values reported in the final column. Consistent with the evidence of the upper panel of Figure 3, this result shows that the variance reduction is concentrated in the business cycle frequency. The inflation rate also shows an evident reduction in volatility in the business cycle frequency.

Following Ahmed et al. (2004), we select several components of GDP growth that are relevant to business cycle policy and the good practices hypothesis, and report the estimates in

[15] Our major results remain unchanged using both 1993 and 1994 as the break point.

Table 2. For example, business cycle policies are more likely to influence the volatility of primary sector production, final sales and investment. Secondary sector production and inventory growth are more sensitive to improved inventory practices. Table 2 shows that final sales and investment significantly decline in the business cycle and high frequencies, that the decline in the variance of primary sector production is concentrated in the business cycle and low frequencies, and that the variance of inventory falls substantially in the business cycle frequency.

To investigate the driving force of the spectrum shifts, we present the estimates of the integrated normalized spectrum in Table 3. For the real GDP growth rate, the reduction of output volatility appears to be even across the three different frequency ranges. The inflation rate also shows a similar result. Consistent with the good luck hypothesis, our result implies that the decline in shocks hitting the economy accounts for much of the output volatility reduction.

Turning to the selected components of GDP growth, we see that final sales and investment have no significant shifts in the normalized spectrum. Hence business cycle volatilities in these variables are not significantly lower than at other frequencies. Looking at the production components, the decline in the growth of primary sector output appears to be concentrated in the business cycle frequency, implying that business cycle practice plays an important role in smoothing the growth of primary sector production. We interpret this effect as a reflection of government commitment to promote growth in the agricultural sector. There is no evidence of shifts in the normalized spectrum of secondary sector output and inventory implying that improved inventory practice has no significant effect on smoothing output volatility. These results reinforce the good luck hypothesis.

<Insert Table 2 here>

<Insert Table 3 here>

In summary, our results show that the volatilities of the real GDP growth rate and the inflation rate have declined since the mid-1990s. Although policy effectiveness has improved through market-oriented reforms over the last three decades, the spectra do not show a significant reduction in the business cycle frequency band. Meanwhile, no strong evidence is obtained in support of better business practice being the source of the economic moderation in China, aside from in primary sector production. The good luck hypothesis, which suggests a reduction in the variance of the exogenous shocks hitting the economy, provides the more plausible explanation for the declining macroeconomic volatility.

4. Vector Autoregression Analysis

The results of our frequency domain analysis suggest that milder shocks contribute most to volatility reduction, however it cannot rule out the possibility of structural change which may manifest as a part of the spectra reduction. To complement the frequency domain analysis, we identify a variety of VAR models, and implement a series of counterfactual analyses on the origin of the volatility reduction. As Sims (1992) suggests, a VAR analysis can allow us to understand the changes of transmission mechanisms in business cycle practices and monetary policy, and their impacts on reducing volatilities. We can investigate how important the reduction in random shocks is.

4.1 Reduced-form VAR

Our basic VAR model is similar to the small-scale model of Mehrotra (2007) in that it includes real GDP growth rate, inflation rate, the percentage change of NEER, and the interest rate. Real GDP growth rate and the CPI inflation rate are representative variables for tracking general economic performance. The NEER, or the trade weighted exchange rate, is used to capture more comprehensively the effectiveness of exchange rate policy. The monetary policy instrument, interest rate, is the lending rate determined by the central bank.[16]

To check the robustness of our results, we extend the basic model into a five-variable function by distinguishing between final sales and inventory. As Ahmed et al. (2004) suggest, the five-variable model examines the role of business cycle policies and inventory practices directly. For example, improved inventory management leads to lower inventory volatility, which may also contribute to a reduction in the variance of the real GDP growth rate. The lag structure of the VAR system has been selected according to the AIC criteria. The optimal lag length is two for both four-variable and five-variable VAR models. Meanwhile, we only include a constant intercept term without a time trend.

To investigate the stability of the parameters in the VAR models above, we conduct both the Chow test of coefficient stability and the Goldfeld-Quandt test of standard errors (Goldfeld and

[16] Monetary aggregate could also be used as a measure of monetary policy instrument, as quantitative methods are still the key instruments for China's government (Goodfriend and Prasad, 2007). Hence, we use the growth rate of M2 money supply as an alternative measure of monetary policy instrument. Our primary results are essentially same. These results are not reported, but are available upon request.

Quandt, 1965). Under the alternative hypotheses of these tests, the VAR parameters experience a discrete shift across the two periods.

The test results for coefficient stability are reported in Table 4. In the four-variable model, the *p*-value applied to the GDP and inflation equations, for the null hypothesis of no change, are 0.077 and 0.060, rejecting the null hypothesis at the significance level of 10%. Only the interest rate equation appears to display coefficient stability. The structural change is further emphasized in the five-variable model as null hypotheses are rejected at the significance level of 5%, implying that all equations have coefficient instability across the two periods.

The standard deviations of the error terms and the volatility breaks test are reported in Table 5. There is clear evidence that all these equations display much less volatility in the Period II. The VAR analyses show that there are both substantial changes in economic structure and in volatility reduction, and so we cannot separate the individual effects of the three hypotheses to explain the aggregate volatility reduction.

<Insert Table 4 here>

<Insert Table 5 here>

To quantify the relative contribution of each hypothesis, we follow the method of Stock and Watson (2002) and Ahmed et al. (2004), and use VAR models to estimate the unconditional variances of each variable. The first and second rows of Table 6 present the shocks of each period and the corresponding coefficients used to compute the unconditional variance. The counterfactual exercises are reported in the third and fourth rows, and estimate the unconditional variance by taking other period shocks into the models for each period. When Period II shocks are substituted into the Period I model, we observe a substantial reduction in output volatility as the standard deviation falls from 4.12 to 2.42. Similarly, when the Period II model is subject to Period I shocks, output volatility increases from 1.87 to 2.92. As a result, the milder shocks account for most of the reduction of output volatility from Period I to Period II (from 47 percent to 76 percent). The results for inflation are similar to those of output. As shown in Table 6, roughly 48 percent to 60 percent of the reduction in inflation volatility is due to a reduction in the number of random shocks. The results from the five-variable model, presented in the bottom panel of Table 6, reinforce these conclusions. The contribution of shocks to the volatility reduction in final sales is roughly 70 percent lending strong support to the good luck hypothesis.

<Insert Table 6 here>

4.2 Structural VAR analysis

To examine what the fundamental disturbances are behind the decrease in reduced-form innovation variances, we impose an economic structure on the VAR impulse response function.

Following Breitung et al. (2004), we consider the following structural VAR model,

$$Ay_t = A_1^* y_{t-1} + \ldots\ldots + A_p^* y_{t-p} + C^* D_t + v_t \tag{4}$$

where y_t is a $(K \times 1)$ vector of endogenous variables, K is the number of variables and p is the order of the VAR model. The term v_t is a $(K \times 1)$ vector of structural shocks that is a zero mean white noise process with time-invariant covariance matrix Σ_v. The invertible matrix A is a $(K \times K)$ non-diagonal matrix allowing the variables to have instantaneous relationships. The matrix A_i^* $(i = 1,2,\cdots, p)$ is the $(K \times K)$ coefficient matrix, and B is the structural parameter matrix. The term D_t is the deterministic vector and C^* is the corresponding coefficient vector. In the present study, the deterministic terms only include constant terms which could be removed by pre-adjusting variables in practice. Therefore, for notational convenience the deterministic term is dropped from the model. We also assume a vector of structural innovations, denoted by ε_t, to be related to the model residuals v_t by a linear equation $v_t = B\varepsilon_t$, where B is a (K × K) matrix and ε_t is mutually independent and follows $N(0, \quad I_k)$.

Ignoring the deterministic terms and replacing v_t by $B\varepsilon_t$, the structural VAR model can be written as

$$Ay_t = A_1^* y_{t-1} + \ldots\ldots + A_p^* y_{t-p} + B\varepsilon_t\,. \tag{5}$$

The reduced form VAR, corresponding to the structural form Equation (5), can be obtained by pre-multiplying with A^{-1}, such that

$$y_t = A_1 y_{t-1} + \ldots\ldots + A_p y_{t-p} + \mu_t$$

where

$$A_i = A^{-1} A_i^*, (i = 1,2,\cdots, p)\,, \tag{6}$$

$$\mu_t = A^{-1} B\varepsilon_t \;. \tag{7}$$

We estimate the above structural model, the so-called *AB-model* in Amisano and Giannini (1997), with a set of parameter restrictions using a scoring method.

Our analysis is based on the four-variable model of Section 4.1. Following Mehrotra (2007), we impose economic restrictions to identify the structural VAR impulse response functions. The model is comprised of four endogenous variables, namely, the growth rate of real output denoted as y, the percentage change of CPI denoted as p, interest rate denoted as i and the percentage change of the exchange rate denoted as $neer$. The errors of the reduced-form VAR, estimated in Section 4.1, are written as $u_t = (u_t^y,\ u_t^p, u_t^i, u_t^{neer})'$, while the structural shocks are denoted as $\varepsilon_t = (\varepsilon_t^y,\ \varepsilon_t^p, \varepsilon_t^i, \varepsilon_t^{neer})'$. The *AB* model[17] is given by

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ 0 & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{bmatrix} \begin{bmatrix} u_t^y \\ u_t^p \\ u_t^i \\ u_t^{neer} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 \\ 0 & 0 & b_{33} & 0 \\ 0 & 0 & 0 & b_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^p \\ \varepsilon_t^i \\ \varepsilon_t^{neer} \end{bmatrix}. \quad (8)$$

To estimate this system, we need to make an identification assumption based on economic theory. Following Sims and Zha (1995) and Rotemberg and Woodford (1999), we assume that real activities do not react immediately to price and financial variables changes, as the first row of Equation (8) indicates. This assumption is consistent with empirical evidence that the adjustments of real economic activities are subject to inertia and are costly. Due to the rigidity of price adjustments, the second row of Equation (8) specifies that price reacts to financial shocks, i.e., both monetary supply and exchange rate shocks, with a lag. Our specification is consistent with the argument of Rotemberg and Woodford (1999), who suggest that the adjustment of real output and price to monetary shocks occurs with a delay. Capital controls of the RMB, although still pegged to the U.S. dollar, still allow the Chinese monetary authority to have partial independence of monetary policy.[18] Hence, we assume that monetary policy does not react contemporaneously to exchange rate shocks. The monetary policy response function which sets the interest rate after observing the price level but not the exchange rate and the current value of output is identified in the third row of Equation (8). As with Sims and Zha (1995), information delays do not allow a monetary policy response within the period (the quarter in our data) to output growth. Finally, following Kim and Roubini (2000), we assume that the exchange rate in the VAR model responds

[17] We also estimate the structural VAR model based on the five-variable model of Section 4.1. Due to the limitations of economic theory, we use the recursive causal ordering method suggested by Christiano et al. (1999) to identify the VAR system. For simplicity and space, this result is not reported but is available upon request.

[18] Prasad and Rajan (2006) suggest that as the Chinese economy becomes more complex and integrated with the global economy, the restrictions on capital accounts become more porous as evading controls becomes much easier through channels such as trade credit and underground banks.

contemporaneously to all the variables.[19] The exchange rate equation is identified in the fourth row of Equation (8).

Table 7 reports the structural estimates of the *A* and *B* matrix across the two periods. Consistent with our expectations, the estimated values of a_{32} are negative in both periods. This implies that the Chinese monetary authority took a contraction position in response to a shock in the inflation rate. The likelihood ratio of the overidentification test reports that the $\chi^2(1)$ test statistics for Period I and Period II are 1.69 and 2.17, respectively, with corresponding *p*-values of 0.194 and 0.141. This shows that our structural VAR model is not overidentified.

<Insert Table 7 here>

Table 8 reports the results of the counterfactual simulations with structural parameters and shock processes estimated in different periods. It shows that when Period II structural shocks are taken into the Period I economic model, the standard deviation of output growth rate falls dramatically from 4.384 to 2.477. Meanwhile, when Period II's economic structure is subject to Period I's shocks, output volatility increases substantially from 1.947 to 3.101. Roughly 47.4 to 78.2 percent of the reduction in output volatility can be explained by the smaller random shocks. Consistent with our previous findings, our structural VAR analysis confirms that reduced shocks hitting the economy contributes the most to the decline in volatility in the post-1994 period; the good luck hypothesis finds further support.

<Insert Table 8 here>

5. Conclusion

The economic volatilities observed in China have been markedly lower since the mid-1990s. We analyze three possible explanations for this economic moderation: good policy, good business practices and milder economic shocks. In particular, we investigate their respective contributions to the decline in macroeconomic volatility by using frequency domain and VAR analysis. The results of our frequency domain analysis show that most of the variance reduction of real GDP growth rate and CPI inflation rate is due to smaller shocks to the economy. Better policy and business cycle practices have only a marginal impact on smoothing economic volatility.

To complement the frequency domain analysis, we use a standard VAR model, and conduct a counterfactual analysis to further investigate the role of good policy and business practices in

[19] Kim and Roubini (2000) suggest that the exchange rate is a forward-looking asset price. The exchange rate equation is an arbitrage equation describing the financial market equilibrium.

smoothing the economy. Still, the results are consistent with the good luck hypothesis, i.e., that reduced random shocks account for most of the reduction in output volatility. Our results are robust for either a structural VAR model or a five-variable model that distinguishes between final sales and inventory.

Our results have a number of policy implications and call into question the sustainability of the growth of China's economy. Over the last three decades, the growth of the Chinese economy has been remarkable, but heavily reliant on its incremental and experimental approach to economic reform. This reform is underpinned by a dual track, where a planned track is maintained while introducing a market track, which provides opportunities for economic agents to be better off without creating losers in absolute terms (Lau et al. 2000).

This strategy serves China well during the reform period, but it involves a number of institutional distortions and constraints (Prasad and Rajan, 2006). For example, although reformed, China's currency regime is still de facto inflexible, and extensive capital controls remain. Most funds are channeled to SOEs at a cheap interest rate, while small- and medium-sized enterprises have limited financing opportunities from bank loans and capital markets. As China becomes more developed and complex, numerous institutional deficiencies and policy distortions may themselves become a source of instability, and eventually reduce the capacity of the Chinese economy to withstand and recover against any large economic shocks (Prasad, 2008).

Although Chinese economic growth is high and relative stable in the post-1994 period, our results indicate that this is largely due to good luck, or to milder shocks to the Chinese economy. Nevertheless, good luck has a tendency to run out and subsequent bad luck would severely disrupt the Chinese economy and social stability. China needs to improve its resilience to large shocks before this happens. Perhaps the best way forward is for China to develop more flexible, market-based policy tools as well as to reduce resource misallocation by channeling more funds to the private sector.[20] Well-designed government policies aimed at improving policy effectiveness and business practices will allow the Chinese economy to cope with any unforeseen risks, or bad luck, and will ensure the sustainable growth of China's economy.

[20]Hsieh and Klenow (2009) provide evidence that adjusting China's resource allocation to reflect U.S. efficiency would increase total factor productivity by 30 to 50 percent.

Appendix. Data Description

This paper employs quarterly data series from the first quarter of 1979 to the fourth quarter of 2010. Most of the data are from the CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). As several quarterly series of variables are not available before 1992, we first draw yearly series of these variables from CEIC, and then use the Chow-Lin (1971) method for temporal disaggregation by transforming series from annually into quarterly. Variables are seasonally adjusted by the Census X-12 ARIMA method. Growth rate refers to the quarterly year-on-year growth rate. The data we use in this paper are reported below.

No.	Data Series	Source
1	Growth Rate of Real GDP	Abeysinghe and Rajaguru (2004) before 1992, CEIC after 1992.
2	Growth Rate of Real Primary Industry Products	Yearly observations are drawn from CEIC, and are transformed from annually to quarterly before 1992. Quarterly observations are drawn from CEIC after 1992.
3	Growth Rate of Real Secondary Industry Products	Yearly observations are drawn from CEIC, and are transformed from annually to quarterly before 1992. Quarterly observations are drawn from CEIC after 1992.
4	Growth Rate of Real Tertiary Industry Products	Yearly observations are drawn from CEIC, and are transformed from annually to quarterly before 1992. Quarterly observations are drawn from CEIC after 1992.
5	Consumer Price Index	Yearly observations are drawn from CEIC, and are transformed from annually to quarterly before 1985. Quarterly observations are drawn from CEIC after 1985.
6	Final Sales Growth	The growth rate of Retail Sales of Consumer Goods. Yearly observations are drawn from CEIC, and are transformed from annually to quarterly before 1985. Quarterly observations are drawn from CEIC after 1985. Deflated by the Consumer Price Index.
7	Fixed Asset Investment Growth	Yearly observations are drawn from CEIC, and are transformed from annually to quarterly before 1985. Quarterly observations are drawn from CEIC after 1985. Deflated by the GDP deflator.
8	Inventory Growth	Yearly observations are drawn from CEIC, and are transformed from annually to quarterly. Deflated by the GDP deflator.
9	Nominal Effective Exchange Rate (NEER)	CEIC
10	Interest Rate	One-year lending rate, CEIC.

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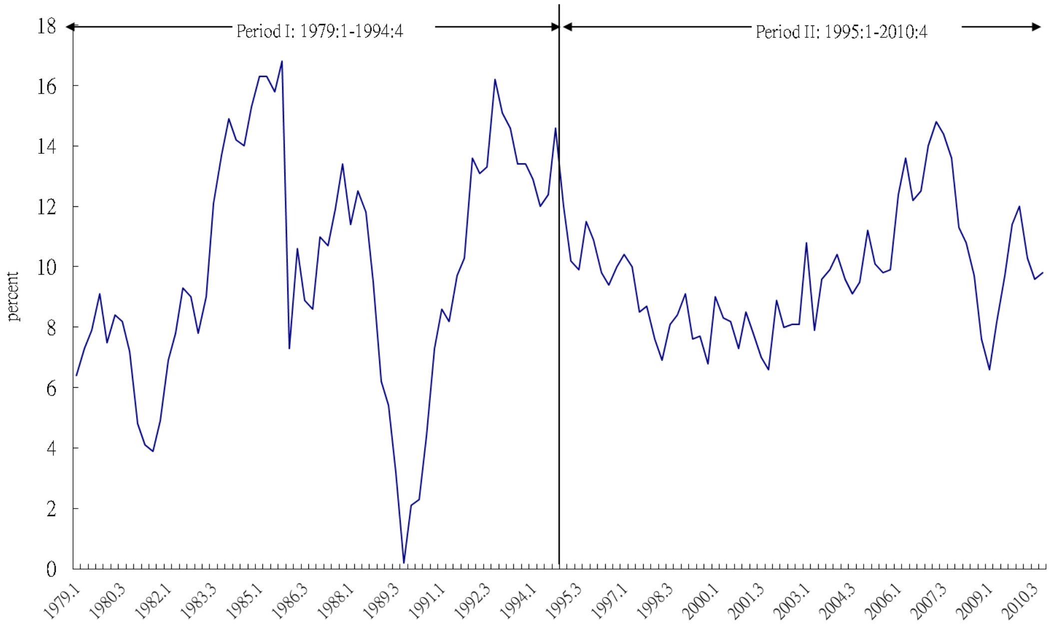
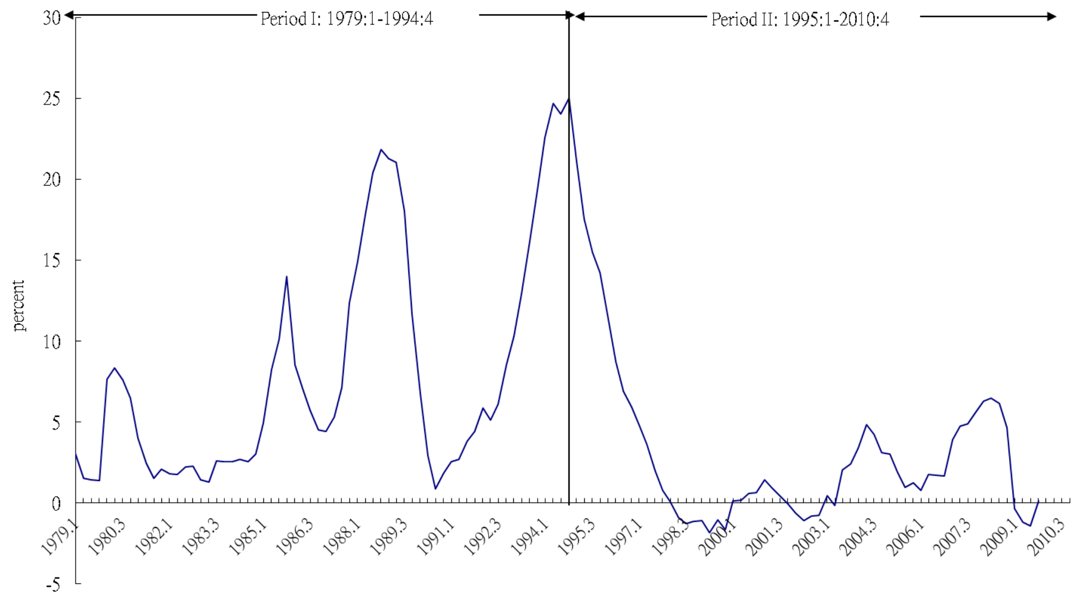
Figure 1. Real GDP (Quarterly Year-on-Year Growth Rates)



Data source: Abeysinghe and Rajaguru (2004) before 1992; CEIC database after 1992.

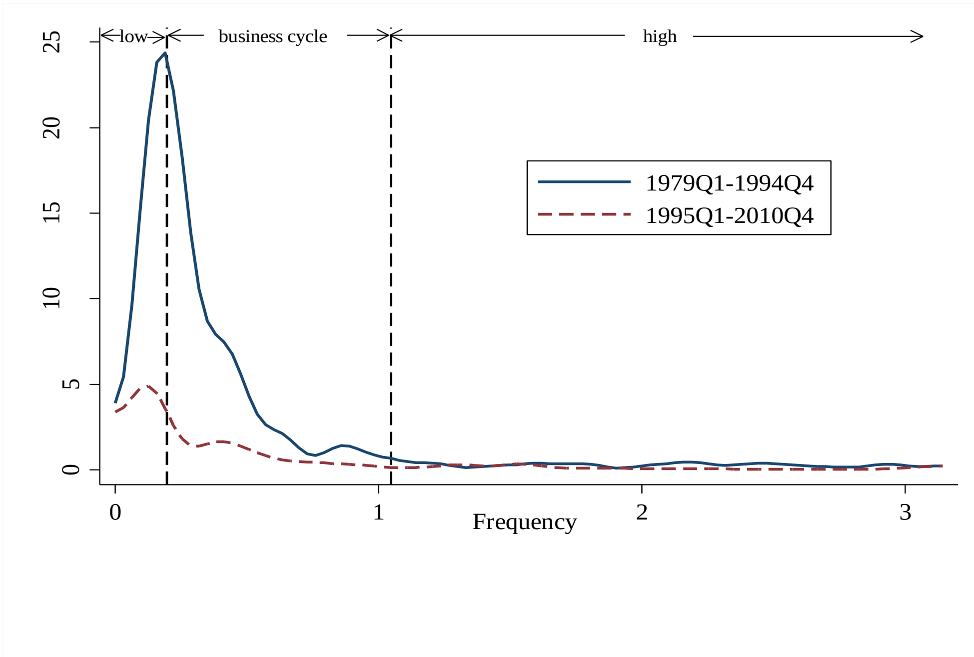
Figure 2. Consumer Price Index (Quarterly Year-on-Year Growth Rates)



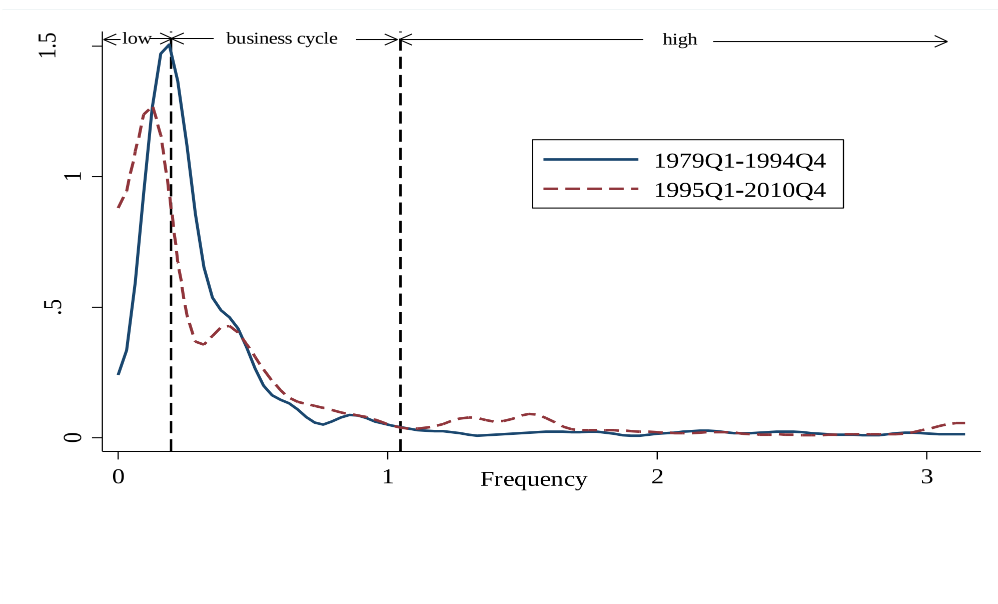
Data source: CEIC database (the observations before 1985 are transformed from annual data by the Chow-Lin (1971) method since quarterly data are available only after 1985).

Figure 3. Real GDP

Spectrum

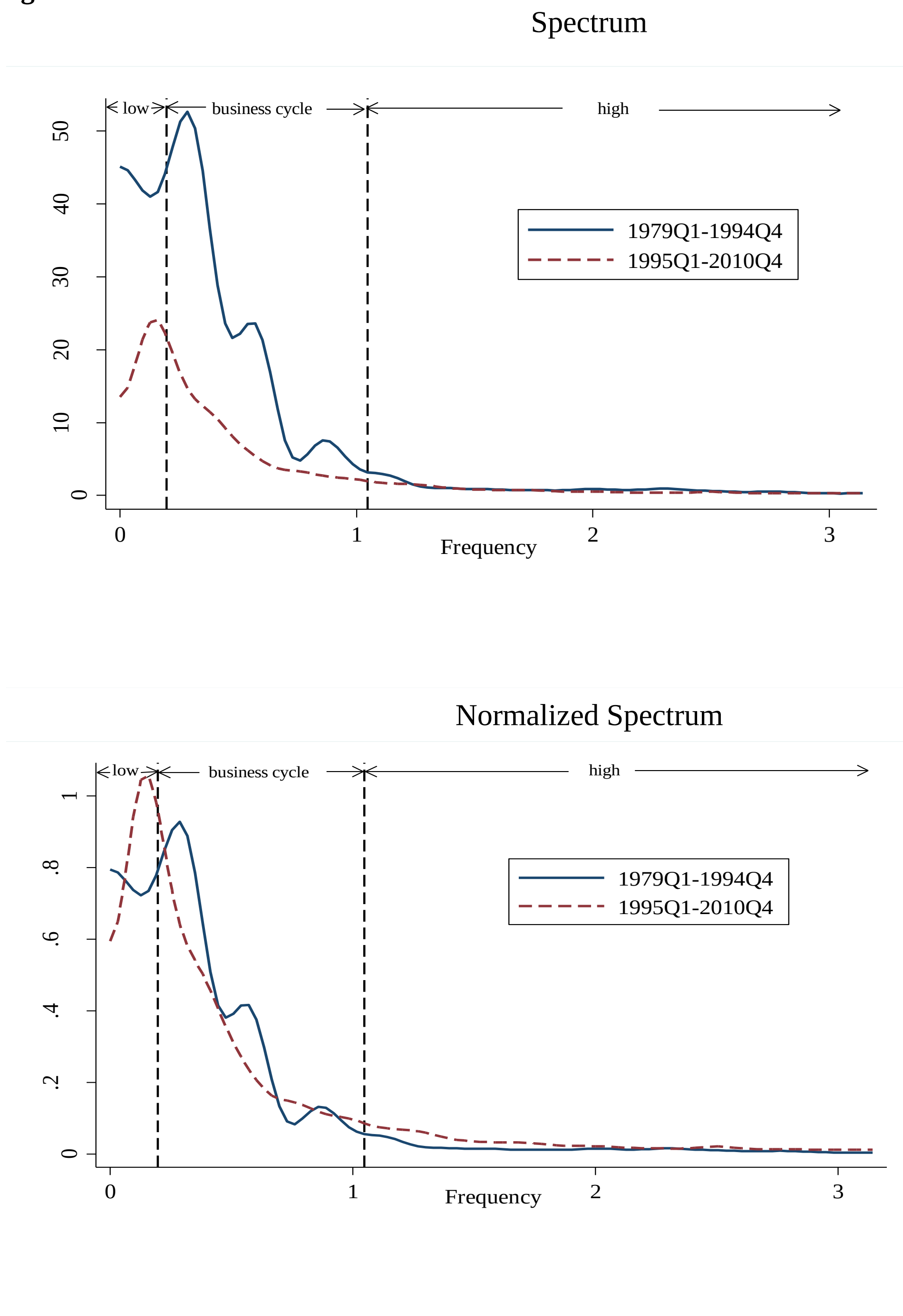


Normalized Spectrum



Note: Following Ahmed et al. 2004, the whole spectrum is separated into three frequency bands, namely low, business cycle and high. The business cycle is assumed to last between 6 quarters and 32 quarters, corresponding to a frequency range between $\pi/16$ and $\pi/3$. Cycles longer than 32 quarters (frequency ω smaller than $\pi/16$) will fall into the low-frequency range, and cycles shorter than 6 quarters (frequency ω larger than $\pi/3$) are classified as in the high-frequency range. Data source: Abeysinghe and Rajaguru (2004) before 1992; CEIC database after 1992.

Figure 4. Consumer Price Index



Note: Following Ahmed et al. 2004, the whole spectrum is separated into three frequency bands, namely low, business cycle and high. The business cycle is assumed to last between 6 quarters and 32 quarters, corresponding to a frequency range between $\pi/16$ and $\pi/3$. Cycles longer than 32 quarters (frequency ω smaller than $\pi/16$) will fall into the low-frequency range, and cycles shorter than 6 quarters (frequency ω larger than $\pi/3$) are classified as in the high-frequency range. Data source: CEIC database (the observations before 1985 are transformed from annual data by the Chow-Lin (1971) method since quarterly data are available only after 1985).

Table 1. Means and Standard Deviations for Quarterly Year-on-Year Growth Rates

	Mean		Difference	Standard Deviation		Difference
	Period I	Period II		Period I	Period II	
GDP	9.98	9.71	-0.27	4.02	1.96	-2.06
Inflation	8.18	2.97	-5.21	7.53	4.77	-2.76
Inventory	8.61	5.37	-3.24	2.41	2.32	-0.09
Primary Output	5.20	4.01	-1.18	3.97	1.94	-2.02
Secondary Output	11.99	11.11	-0.89	7.66	2.34	-5.32
Tertiary Output	11.46	10.59	-0.87	6.31	2.25	-4.06
Final Sales	8.88	13.37	4.49	7.71	3.51	-4.21
Investment	17.31	17.80	0.49	38.22	10.67	-27.55
Interest Rate	8.02	6.82	-1.20	1.92	2.04	0.11
NEER	-6.00	1.71	7.71	13.52	5.47	-8.05

Note: We consider macroeconomic time series data from the first quarter of 1979 to the last quarter of 2010. NEER denotes the nominal effective exchange rate. Total observations are 128. We use the last quarter of 1994 as the break point to separate the sample into two periods: Period I (1979:Q1-1994:Q4) and Period II (1995:Q1-2010:Q4). All variables are quarterly year-on-year growth rate and are seasonally adjusted. Most of the data are drawn from CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). When quarterly data are not available, we transform series from annually into quarterly by the Chow-Lin (1971) method. See Appendix for details on data source and variable definition.

Table 2. Estimates of Integrated Spectrum

		Integrated Spectrum			
Variable	Frequency Interval	Period I	Period II	Test	*p*-value
GDP	Low	7.09	2.00	0.92	0.18
	Business Cycle	7.86	1.30	1.75	0.04
	High	0.99	0.49	0.31	0.38
Inflation	Low	16.35	8.96	0.75	0.23
	Business Cycle	36.76	11.10	2.27	0.01
	High	2.73	2.34	0.07	0.47
Primary Output	Low	3.44	0.80	1.51	0.07
	Business Cycle	10.65	0.97	3.88	0.00
	High	1.40	1.94	-0.36	0.64
Secondary Output	Low	12.58	2.17	1.32	0.09
	Business Cycle	31.62	2.48	3.50	0.00
	High	13.63	0.74	2.84	0.00
Tertiary Output	Low	12.90	1.72	1.50	0.07
	Business Cycle	12.55	2.10	3.39	0.00
	High	13.75	1.17	3.64	0.00
Final Sales	Low	10.75	4.63	1.06	0.15
	Business Cycle	33.85	5.22	3.34	0.00
	High	13.96	2.25	2.22	0.01
Investment	Low	163.77	10.98	1.27	0.10
	Business Cycle	428.59	28.54	1.95	0.03
	High	845.93	72.64	2.14	0.02
Inventory	Low	2.85	4.03	-0.42	0.66
	Business Cycle	2.84	1.21	1.42	0.08
	High	0.00	0.04	-0.04	0.52

Note: We consider macroeconomic time series data from the first quarter of 1979 to the last quarter of 2010. NEER denotes the nominal effective exchange rate. Total observations are 128. We use the last quarter of 1994 as the break point to separate the sample into two periods: Period I (1979:Q1-1994:Q4) and Period II (1995:Q1-2010:Q4). All variables are quarterly year-on-year growth rate and are seasonally adjusted. Low frequency range = $(0, \pi/16)$; Business cycle frequency range = $(\pi/16, \pi/3)$; High frequency range = $(\pi/3, \pi)$. *P*-value is the marginal significance level of the test. Most of the data are drawn from CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). When quarterly data are not available, we transform series from annually into quarterly by the Chow-Lin (1971) method. See Appendix for details on data source and variable definition.

Table 3. Estimates of Integrated Normalized Spectrum

		Integrated Normalized Spectrum			
Variable	Frequency Interval	Period I	Period II	Test	*p*-value
GDP	Low	0.44	0.53	-0.31	0.62
	Business Cycle	0.49	0.34	0.62	0.27
	High	0.06	0.13	-0.50	0.69
Inflation	Low	0.29	0.40	-0.53	0.70
	Business Cycle	0.66	0.50	0.81	0.21
	High	0.05	0.10	-0.42	0.66
Primary Output	Low	0.22	0.22	0.04	0.48
	Business Cycle	0.69	0.26	2.94	0.00
	High	0.09	0.52	-3.22	1.00
Secondary Output	Low	0.22	0.40	-0.95	0.83
	Business Cycle	0.55	0.46	0.46	0.32
	High	0.24	0.14	0.76	0.22
Tertiary Output	Low	0.33	0.34	-0.08	0.53
	Business Cycle	0.32	0.42	-0.68	0.75
	High	0.35	0.23	0.86	0.19
Final Sales	Low	0.18	0.38	-1.11	0.87
	Business Cycle	0.58	0.43	0.86	0.19
	High	0.24	0.19	0.40	0.34
Investment	Low	0.11	0.10	0.19	0.42
	Business Cycle	0.30	0.25	0.44	0.33
	High	0.59	0.65	-0.53	0.70
Inventory	Low	0.50	0.76	-1.09	0.86
	Business Cycle	0.50	0.23	1.18	0.12
	High	0.00	0.01	-0.05	0.52

Note: We consider macroeconomic time series data from the first quarter of 1979 to the last quarter of 2010. NEER denotes the nominal effective exchange rate. Total observations are 128. We use the last quarter of 1994 as the break point to separate the sample into two periods: Period I (1979:Q1-1994:Q4) and Period II (1995:Q1-2010:Q4). All variables are quarterly year-on-year growth rate and are seasonally adjusted. Low frequency range = $(0, \pi/16)$; Business cycle frequency range = $(\pi/16, \pi/3)$; High frequency range = $(\pi/3, \pi)$. *P*-value is the marginal significance level of the test. Most of the data are drawn from CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). When quarterly data are not available, we transform series from annually into quarterly by the Chow-Lin (1971) method. See Appendix for details on data source and variable definition.

Table 4. Stability Tests of Reduced-form VAR Coefficients

Variable	*F*-statistic	*p*-value
	Four-Variable Quarterly Model	
GDP	1.790	0.077
Inflation	1.892	0.060
Interest Rate	0.966	0.471
NEER	6.447	0.000
	Five-Variable Quarterly Model	
Final Sales	2.234	0.017
Inflation	2.241	0.017
Inventory	3.219	0.001
Interest Rate	2.060	0.029
NEER	4.595	0.000

Note: We consider macroeconomic time series data from the first quarter of 1979 to the last quarter of 2010. NEER denotes the nominal effective exchange rate. Total observations are 128. We use the last quarter of 1994 as the break point to separate the sample into two periods: Period I (1979:Q1-1994:Q4) and Period II (1995:Q1-2010:Q4). All variables are quarterly year-on-year growth rate and are seasonally adjusted. The *F*-statistic is the Chow test statistic for the stability of the coefficients. Most of the data are drawn from CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). When quarterly data are not available, we transform series from annually into quarterly by the Chow-Lin (1971) method. See Appendix for details on data source and variable definition.

Table 5. Innovations From Reduced-form VAR

	Standard Deviation			Test	
Variable	Period I	Period II	% change	*F*-stat.	*p*-value
		Four-Variable Quarterly Model			
GDP	1.66	1.15	-30.56	2.07	0.00
Inflation	2.27	0.82	-63.80	7.63	0.00
Interest Rate	0.49	0.38	-20.87	1.60	0.03
NEER	6.49	2.61	-59.75	6.17	0.00
		Five-Variable Quarterly Model			
Final Sales	5.07	2.26	-55.49	5.05	0.00
Inflation	2.22	0.89	-60.08	6.28	0.00
Inventory	0.23	0.14	-37.60	2.57	0.00
Interest Rate	0.48	0.36	-24.52	1.76	0.01
NEER	6.62	2.78	-58.00	5.67	0.00

Note: We consider macroeconomic time series data from the first quarter of 1979 to the last quarter of 2010. NEER denotes the nominal effective exchange rate. Except for the interest rate, all other variables are quarterly year-on-year growth rate and are seasonally adjusted. Total observations are 128. We use the last quarter of 1994 as the break point to separate the sample into two periods: Period I (1979:Q1-1994:Q4) and Period II (1995:Q1-2010:Q4). *F*-stat. is the *F*-statistic testing for the equality of innovation variances in these two periods. Most of the data are drawn from CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). When quarterly data are not available, we transform series from annually into quarterly by the Chow-Lin (1971) method. See Appendix for details on data source and variable definition.

Table 6. Unconditional Standard Deviation Using VAR

		Four-Variable Quarterly Model			
Coefficients	Shocks	GDP	CPI	Interest Rate	NEER
Period I	Period I	4.12	8.10	1.79	14.43
Period II	Period II	1.87	2.55	1.17	5.04
Period I	Period II	2.42	4.80	1.44	10.19
Period II	Period I	2.92	5.22	1.89	11.39

		Five-Variable Quarterly Model				
Coefficients	Shocks	Final Sales	CPI	Inventory	Interest Rate	NEER
Period I	Period I	8.58	10.72	2.91	2.60	18.24
Period II	Period II	3.48	2.66	1.82	1.07	4.92
Period I	Period II	3.90	5.08	1.77	1.44	9.11
Period II	Period I	7.05	5.44	3.22	1.94	11.86

Note: We consider macroeconomic time series data from the first quarter of 1979 to the last quarter of 2010. NEER denotes the nominal effective exchange rate. Except for the interest rate, all other variables are quarterly year-on-year growth rate and are seasonally adjusted. Total observations are 128. We use the last quarter of 1994 as the break point to separate the sample into two periods: Period I (1979:Q1-1994:Q4) and Period II (1995:Q1-2010:Q4). Most of the data are drawn from CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). When quarterly data are not available, we transform series from annually into quarterly by the Chow-Lin (1971) method. See Appendix for details on data source and variable definition.

Table 7. Estimates of Structural Parameters

Parameter	Period I		Period II	
	Coefficient	S.E.	Coefficient	S.E.
A_21	-0.492	0.162	-0.194	0.087
A_41	-0.516	0.488	0.630	0.254
A_32	-0.022	0.027	-0.072	0.059
A_42	0.832	0.359	0.822	0.361
A_43	-4.192	1.567	1.517	0.744
B_11	1.676	0.151	1.164	0.105
B_22	2.136	0.192	0.798	0.072
B_33	0.487	0.044	0.383	0.034
B_44	6.012	0.540	2.243	0.201
Chi-squared	1.69		2.17	
p-value	0.194		0.141	

Note: We use the last quarter of 1994 as the break point to separate the sample into two periods: Period I (1979:Q1-1994:Q4) and Period II (1995:Q1-2010:Q4). The chi-squared test is the overidentification test for the structural VAR model. Most of the data are drawn from CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). When quarterly data are not available, we transform series from annually into quarterly by the Chow-Lin (1971) method. See Appendix for details on data source and variable definition.

Table 8. Unconditional Standard Deviation Using SVAR

		Four-Variable Quarterly Model			
Parameters	Shocks	GDP	CPI	Interest Rate	NEER
Period I	Period I	4.384	8.752	2.068	16.381
Period II	Period II	1.947	2.656	1.153	5.280
Period I	Period II	2.477	5.008	1.605	10.624
Period II	Period I	3.101	5.506	2.038	12.838

Note: We consider macroeconomic time series data from the first quarter of 1979 to the last quarter of 2010. NEER denotes the nominal effective exchange rate. Except for the interest rate, all other variables are quarterly year-on-year growth rate and are seasonally adjusted. Total observations are 128. We use the last quarter of 1994 as the break point to separate the sample into two periods: Period I (1979:Q1-1994:Q4) and Period II (1995:Q1-2010:Q4). Most of the data are drawn from CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). When quarterly data are not available, we transform series from annually into quarterly by the Chow-Lin (1971) method. See Appendix for details on data source and variable definition.

Statement on revisions made to “Recent Macroeconomic Stability in China" (CER-120830b)

Response to Editorial Assistant’s Comments

Reviewers' comments:
Editorial Assistant: Please add a note at the bottom of each of the figures (Figures 1-4) and tables (Tables 1-8) describing the source(s) for the data used in the figures/tables. Since the appendix contains a description of the data sources, it may be easiest to simply refer the reader to the appendix in each of the notes.

Response: Thank you very much for your comments which helped us to further clarify the paper. In this revised version, we have added a note at the bottom of each of the figures (Figures 1-4) and tables (Tables 1-8) to state the data source.

Specifically, in Page 23, under Figure 1, we added: “Data source: Abeysinghe and Rajaguru (2004) before 1992; CEIC database after 1992.”

In the same page, under Figure 2, we added: “Data source: CEIC database (the observations before 1985 are transformed from annual data by the Chow-Lin (1971) method since quarterly data are available only after 1985).”

In Page 24, under Figure 3, we added: “Data source: Abeysinghe and Rajaguru (2004) before 1992; CEIC database after 1992.”

In Page 25, under Figure 4, we added: “Data source: CEIC database (the observations before 1985 are transformed from annual data by the Chow-Lin (1971) method since quarterly data are available only after 1985).”

Through Pages 26-31, under Tables 1-8, we added: “Most of the data are drawn from CEIC database, while the real GDP growth rate is taken from Abeysinghe and Rajaguru (2004). When quarterly data are not available, we transform series from annually into quarterly by the Chow-Lin (1971) method. See Appendix for details on data source and variable definition.”